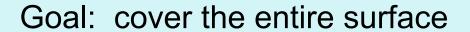
#### Global optimization software library for research and education

#### Nadia Udler

- Created for students and researchers
- Has its roots in potential theory
- Optimization methods with desired properties are created based on basic modules, by varying parameters of generalized algorithm
- Allows
- to design optimization methods with guaranteed convergence but without the use of derivatives of objective function
- to compare existing optimization methods
- to understand principles of learning algorithms
- to design custom variations or hybrids of known heuristic optimization methods.

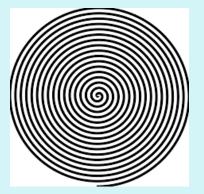
**Example 1 : Vacuum cleaners** 



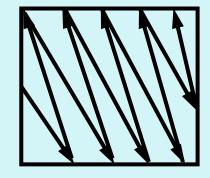
Possible strategies











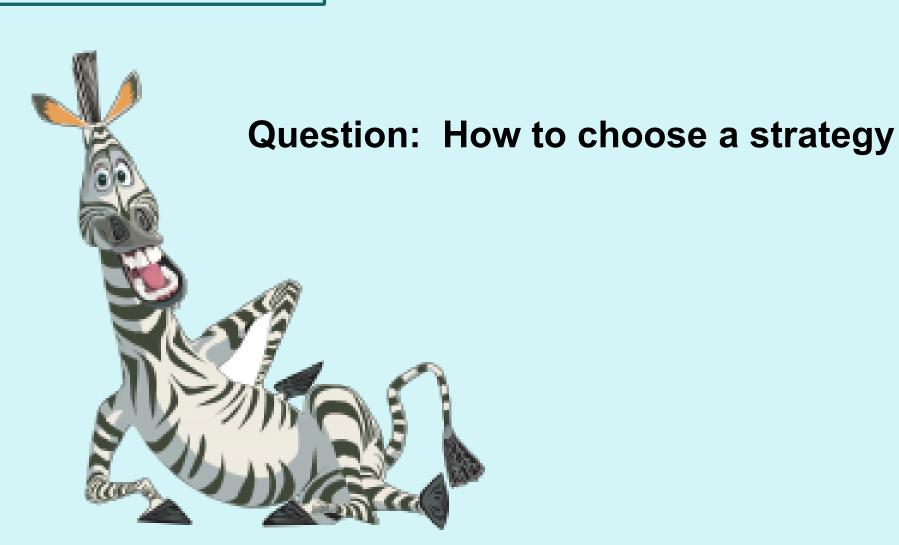
Spiral-like motion from inside

Spiral-like motion from inside

90-degrees zigzaglike motion

30-degrees zigzag-like motion

**Example 1 : Vacuum cleaners** 



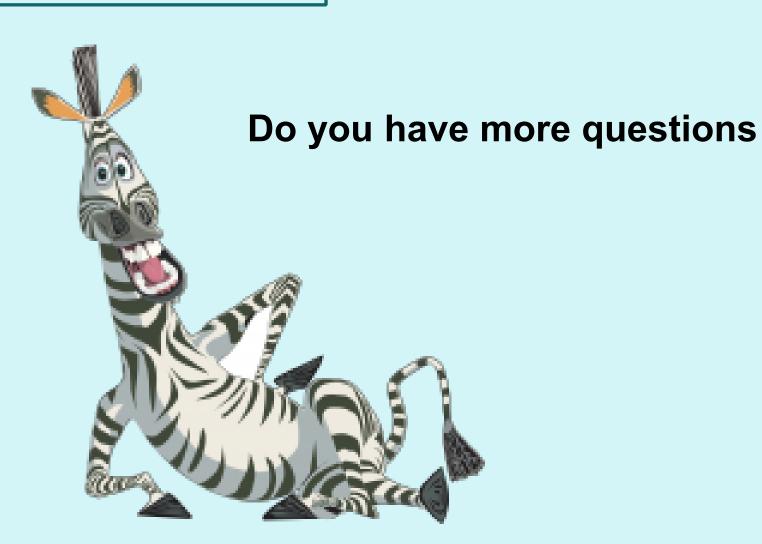
**Example 1 : Vacuum cleaners** 

**Question: How to choose a strategy** 

#### **Possible Answer:**

- 1. Let user to navigate the vacuum cleaner
- 2. Have several buttons on the vacuum cleaner to let the user to switch between the strategies (automatic VC)
- 3. Let vacuum cleaner choose the best strategy ( Al solution)

**Example 1 : Vacuum cleaners** 



**Example 1 : Vacuum cleaners** 

Question: what are important things to consider if the user has to come up with best strategy

- 1. What is the goal
- 2. What are the constraints
- 3. What is the surface
- 4. .....

How easy is it to judge if selected strategy is the best? Or good enough? Or better than the other strategy? It would be nice to have a systematic approach to compare strategies!

#### **Example 1 : Vacuum cleaners**



## Selecting optimal path

**Example 2: find the best path down from the top of the mountain** 



Strategy 1 -



Strategy 2 -->



Strategy 3 →

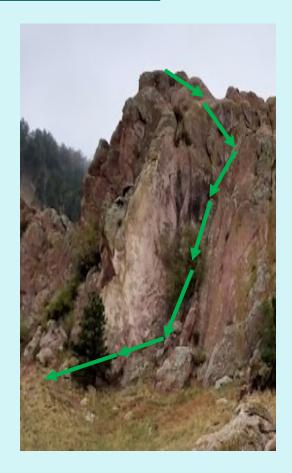


## Selecting optimal path

**Example 2: find the best path down from the top of the mountain** 









Strategy 1 →

Strategy 2 -->

Strategy 3 →

## Selecting optimal path

Question: what are important things to consider if the user has to come up with best strategy to come down from the top of the mountain

- 1. What is the goal
- 2. What are the constraints
- 3. What is the surface
- 4. .....

How easy is it to judge if selected strategy is the best? Or good enough? Or better than the other strategy? It would be nice to have a systematic approach to compare strategies!

#### **Our software**

#### why

- 1. It would be nice to have a systematic approach to compare strategies!
- 2. It would be nice to have a way to teach someone to apply and compare such strategies!

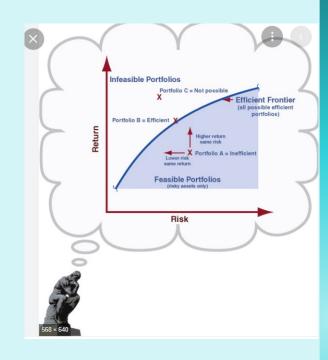
#### how

- 1. Our software is based on the systematic approach to construct global optimization methods (in other words, strategies)
- 2. Our software allows to construct your own strategy based on standard modules provided in the library

## Real word example from finance

More complicated (100+ dimensions)

Portfolio Selection (standard problem in investment)



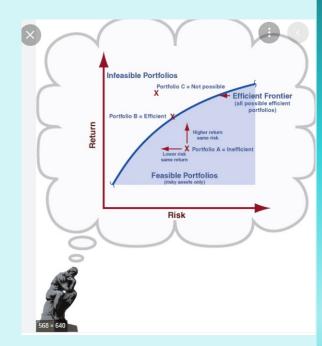
In portfolio selection one finds/compares investment strategies systematically!

Our software can do this, too!

- The portfolio selection problem is concerned with finding an opportfolio x of assets from a given set of n risky assets out of a specified asset universe such that the requirements of the respective investor are met. In general, investors seek to optimize their portfolio in regard of the trade-off between return and risk, such that the meta optimization problem can be formulated as
- minimize Risk(x)
- maximize Return(x)
- This bi-criteria optimization problem is commonly reduced to a single-criteria problem by just focusing on the risk and constraining the required mean, i.e. the investor sets a lower expected return target μ, minimize Risk(x) subject to Return(x) ≥ μ

#### **Measure of risk:**

- L1: Mean Absolute Deviation (MAD)
- L2: Standard Deviation
- Linf: Maxmin
- Distribution based: VaR (value-at-Risk), CVaR (Expected shortfall), Omega
- Entropy based: Rho
- Risk Parity



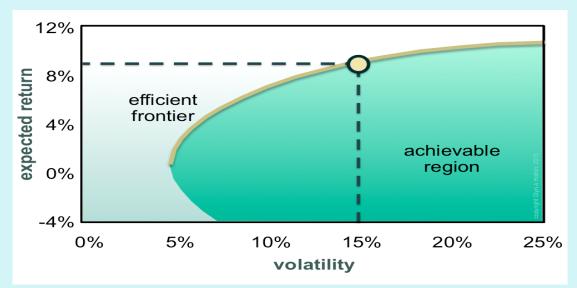
#### Classical approach - Mean Variance Optimization

(Happy Marriage of L2 Risk and Assumption of Normality of Returns)

- Portfolio Volatility as Measure of Risk
- Returns of all market assets are assumed to be multivariate normal with the given vector of means and covariance matrix
- Solution is easy to find

Classical approach - Mean Variance Optimization

#### Markowitz bullet



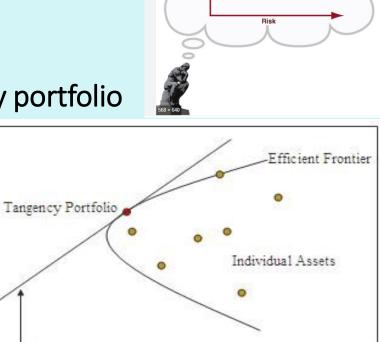
#### Tangency portfolio

Best possible CAL

Standard Deviation

Expected Return

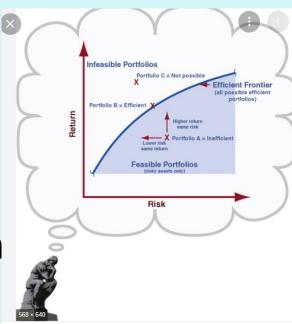
risk free rate



Feasible Portfolios

Classical approach - Mean Variance Optimization

Solving quadratic optimization problem poses num stability challenge!



#### Ways to correct classical approach

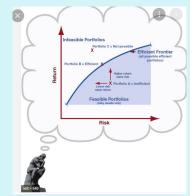
Relax the assumptions of joint normality of returns (possibly take into account higher moments)

Use another risk measure, e.g. MAD, or CVAR

Switching to L1 doesn't help much, portfolios obtained using estimates from a limited set of scenarios are still performing poorly...

One important technique used for practical portfolio purposes are risk-parity portfolios, where the assets are weighted such that they equally contribute risk to the overall risk of the portfolio. Within this approach the focus is on allocation of risk, usually defined as volatility, rather than allocation of capital. The risk parity approach asserts that when asset allocations are adjusted (leveraged or deleveraged) to the same risk level, the risk parity portfolio can achieve a higher Sharpe ratio and can be more resistant to market downturns than the traditional portfolio.

Roughly speaking, the approach of building a risk parity portfolio is similar to creating a minimum-variance portfolio subject to the constraint that each asset (or asset class, such as bonds, stocks, real estate, etc.) contributes equally to the portfolio overall volatility.



• It is sometimes difficult to disentangle the formulation optimization problem and the technicalities of its solut

Efficient Frontier

- Approaches to portfolio optimization become more pre maybe we don't need to seek the optimal solution, but a good one...
- As a result, there is a clear trend to use heuristic optimization methods, and we need a systematic way of generating and combining them...

#### **Next slides - More about our software**

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## Connecting Introductory example with general intent of our software MinPy

Optimization lies at the heart of machine learning and data science.

One of the most relevant problems in machine learning is automatic selection of optimization algorithm depending on the objective.

This is necessary in many applications such as robotics, simulating biological or chemical processes, trading strategies optimization, to name a few.

## Connecting Introductory example with general intent of our software MinPy

Optimization methods in this library work with all objectives including very onerous ones, such as black box functions and functions given by computer code, and the convergence of methods is guaranteed.

Connecting Introductory example with general intent of our software MinPy

This library allows to create customized derivative free learning algorithms with desired properties by combining building blocks from this library or other Python libraries.

#### MinPy code Organization

Minimization – most important class in MinPy. Its methods are building blocks for creating your own optimization strategies.

#### **Attributes**

dim
distribution
initial\_guess
n\_max\_iterations
n\_points
objective\_function
step\_size
tolerance

#### **Methods**

Initialize()
contract()
reflect()
shrink()
update\_m()
update\_c()
stop()

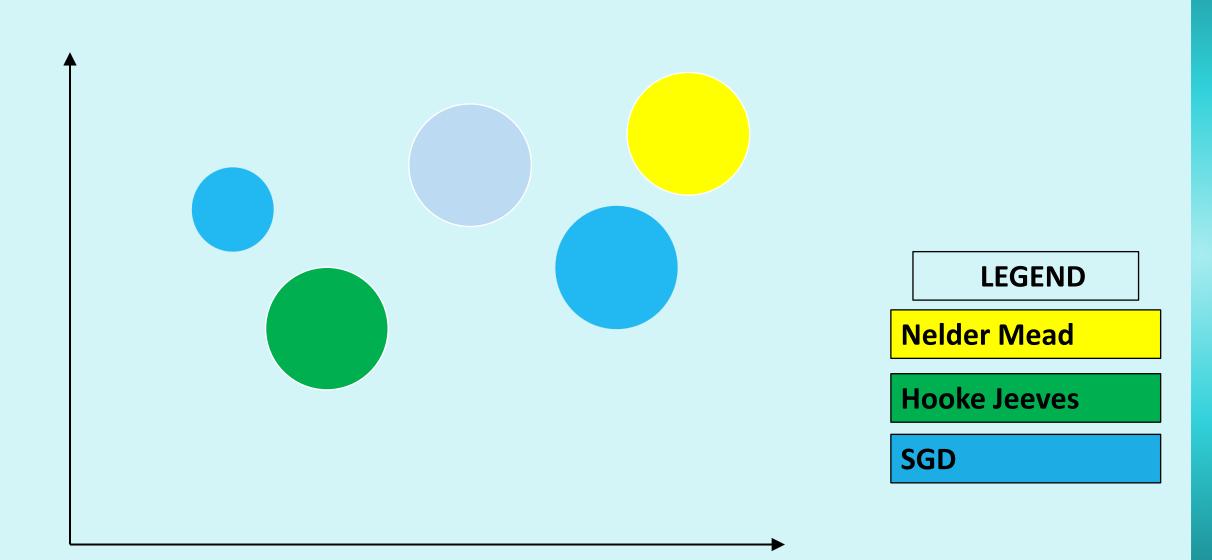
#### MinPy code Organization

A new strategy should be created as follows: Create a class that inherits from Minimization class. Add a method that implements your strategy. It should rely on building blocks from Minimization class that can be used as is or be overwritten.

## For example, below is the code that implements NM\_minimization strategy

```
9 class NM_Minimization(minpy.Minimization):
10
11
12
      def NM stochastic(self):
           self.initialize()
           self.update m()
14
           f m current = self get_f(self.m)
16
           self.compute fu()
17
          count = 0
18
          while not self.stop() and count<=self.maxIter:</pre>
19
20
21
               self.update c()
               self.estimate simplex()
23
               self.update m()
               if self.get f(self.m) >= f m current:
24
                   self.adjust_step(f_m_current)
25
               count = count + 1
26
27
               f m current = self.get f(self.m)
           return self.get best()
28
```

#### **Optimization methods classification**



#### **Optimization methods classification**

